The Application of A Combined Computational Fluid Dynamics (CFD) Artificial Neural Network (ANN) to Increase The Prediction Accuracy of Sediment Grading in Subsea Pipes: A Literature Review.

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ABSTRACT
In recent years, the implementation of subsea pipelines for oil and gas transportation has increased. One of the important aspects of the design process of the subsea pipeline is scour prediction. Scouring causes the subsea pipeline to lose its support and is susceptible to failure due to deflection. This paper presents the result of a literature review of scouring-related research to obtain a method to increase scouring prediction accuracy. Based on the literature research, it is known that the errors found in Computational Fluid Dynamics (CFD) are mainly affected by the flow models. Existing flow models cannot fully represent the complexity of turbulent flow that occurs during the scouring process. Artificial Neural Network (ANN) can reduce the error value. But, the CFD-ANN hybrid methods can potentially decrease the error value by about 20% more than CFD. Therefore, the CFD-ANN hybrid method is expected to be a new method that could be used to predict subsea pipeline scouring in the oil and gas industry.

Keywords:
Scouring, Subsea Pipeline, Computational Fluid Dynamics, Artificial Neural Network, Hybrid Method

1. Introduction

With the growth of marine exploration in the oil and gas sector over the past few decades, the use of subsea pipelines has expanded. The assessment of grinding is one of the key steps in the design and maintenance of subsea pipelines. Environmental factors like currents and/or waves can produce scouring, which can cause underwater plumbing systems to collapse (Chen & Zhang, 2009). Physical testing techniques and a variety of flow and sediment model-building techniques were used to make the first prediction of sediment scour. Some researchers (Monacada-M. & Aguirre-Pe, 1999; Sumer & Fredsøe, 2002) forecast current washout using physical experimental approaches. However, scaling effects for each parameter that affect experimental accuracy are absent in physical
experimental procedures. Consequently, there is a discrepancy between the predicted and actual results. Numerical methods have been adopted as approaches to handle complex problems as computing technology has evolved. Many researchers, including (Cao et al., 2015; Larsen et al., 2016), have employed computational fluid dynamics (CFD), a numerical technique based on the finite volume method (FVM), to forecast subsea pipeline scour. This study shows that CFD can predict scour accurately and provide superior fluid behavior visualization than the outcomes of actual testing. The precision of the simulation findings is however still compromised by an erroneous value. This is brought on by the flow, sediment transport, or mesh quality modeling procedure. Artificial neural networks (ANNs), which have been used by scientists to conduct research into artificial intelligence approaches, are being used to increase prediction accuracy (Azamathulla & Zakaria, 2011; Hu et al., 2020a). This ANN model was created to increase forecast accuracy by looking at data for each significant process in sediment scour production. This lowers the predicted error rate. Even modern academics have created a combined CFD and ANN technique for greater accuracy outcomes. This integrated technique has been applied in a variety of disciplines, including the modeling of fluid mixing events in pipes (Grbic et al., 2020), the simulation of flow parameters in open channel trenches (Gholami et al., 2015), and the prediction of solid particle degradation (Pandya et al., 2017). These research' findings support the combined CFD-ANN approach's extremely low error value. The fluid-sediment interaction model used in the Pandya et al., 2017 study is remarkably similar to the method used to remove sediment from a submerged pipeline. As a result, CFD-ANN technique offers a chance to raise the prediction accuracy of sediment scour in underwater pipelines.

2. Methodology

The method used in this study is literature research, and the working steps are shown in Figure 1. Reference collections based on topics discussed, keyword searches for pipeline scour, computational fluid dynamics, and artificial neural networks, providing a website database of scientific research. The quality of the selected literature was then evaluated in accordance with cutting-edge criteria, the originality and correctness of the data, and the accuracy of the technique and analysis. The literature was chosen in accordance with Scopus indices Q1–Q3.

Figure 1. Our literature review flowchart
3. Results and Discussion

**Computational Fluid Dynamics (CFD) Model to Predict Sediment Scour**

Computational fluid dynamics (CFD) is a numerical technique that transforms physical events into digital data, simulates them as though they were real-world actions, and then transforms the numerical outcomes back into data information. The physical equations (conservation of mass, momentum, and energy) governing fluid motion on each mesh model are solved using CFD as a simulation tool during the sediment scour prediction process. The model parameters, such as the geometry model, flow model, hydrodynamic model, seabed morphology model, and sediment transport model, determine the accuracy of the prediction outcomes during the sediment scour CFD process (Fuhrman et al., 2014). Additionally, when meshing the model into a mesh system, the quality of the meshing and the description of the boundary conditions both affect how well the CFD procedure produces results (Liang & Cheng, 2005).

The first step in creating a CFD is determining the geometric model. The parameters of the pipe’s dimensional characteristics and the size of the sink in use are used to create the geometric model. Additionally, boundary conditions must be established in the simulation to ensure that the calculation outcomes are consistent with the desired outcomes and that the calculation time is minimized (Fuhrman et al., 2014). One of the problems with CFD modelling is mesh size. The CFD model, which is dependent on the turbulence model, is greatly impacted by the quality of meshing (Liang & Cheng, 2005). Predictions of scour depth can be inaccurate and vortex shedding can appear to not occur if the mesh quality is coarse. The best prediction outcomes with very fine mesh quality are produced as a result. However, it should be remembered that computation time increases with meshing quality. CFD modelling of sediment washout due to water flow is discussed in more detail in this study’s discussion of CFD modelling.

In CFD, flow models are created to describe fluid flow patterns and characteristics that influence sediment scour in subsea pipes. This flow model aims to produce predictions for desirable parameters including fluid viscosity, characteristic length, density, and velocity. In Table 1, different flow models, including the latent flow model, the Reynolds-averaged Navier-Stokes (RANS) model, and the Large Eddy Simulation (LES) model, are compared to the results of CFD modelling to forecast the present scour depth.

<table>
<thead>
<tr>
<th>No</th>
<th>Flow model</th>
<th>Scour depth</th>
<th>Scour profile</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Potential flow model</td>
<td>Predictable</td>
<td>Unpredictable</td>
<td>(Li &amp; Cheng, 1999)</td>
</tr>
<tr>
<td>2</td>
<td>RANS model turbulent equation $k-\varepsilon$</td>
<td>Predictable</td>
<td>Less predictable, terutama di bagian belakang pipa</td>
<td>(Lee et al., 2016; Mathieu et al., 2019)</td>
</tr>
<tr>
<td>3</td>
<td>RANS model turbulent equation $k-\omega$</td>
<td>Underestimate</td>
<td>Predictable</td>
<td>(Li et al., 2020; Mathieu et al., 2019)</td>
</tr>
<tr>
<td>4</td>
<td>LES model Smagorinsky’s sub-grid scale</td>
<td>Overpredictable</td>
<td>Overpredictable</td>
<td>(Liang et al., 2005)</td>
</tr>
</tbody>
</table>

Table 1 demonstrates that the potential flow model, RANS model, and LES model have insufficient ability to forecast scour profiles. This is because, despite the fact that vortex shedding during grinding has a substantial impact on the leeward wake process that creates the scour profile, vortex shedding cannot be adequately represented (Zhang et al., 2014). By using the turbulence equations to solve the RANS model or the LES model, one can derive the hydrodynamic description of the horseshoe vortex and vortex shedding (Quezada et al., 2018). A potential flow model that ignores the turbulence equation cannot therefore provide reliable predictions.
The turbulence model based on the RANS equation is more extensively utilized in industry since the LES model requires more processing power and more intricate implementation. Because turbulence equations-based RANS models have improved performance and are more widely applicable (Mishra & Aharwal, 2018).

In the meantime, Figure 2 provides more information on the RANS model between the $k$-$\varepsilon$ turbulence model and the $k$-$\omega$ turbulence model. The RANS model with the $k$-$\omega$ turbulence equation produces forecasts that are smaller than the experimental results but produces superior predictions of scour depth, as can be seen in the figure. Relatively accurate downstream of the pipeline. The scour depth is still difficult to forecast using even the most practical $k$-$\varepsilon$ turbulence models (Mathieu et al., 2019). Additionally, the erosion of silt in the pipeline's downstream region is another unpredictability of the $k$-$\varepsilon$ turbulence model. As the water flow reaches the sediment boundary layer, the originally positive cross-diffusion effect progressively changes to a negative one, resulting in this disparity. The flow at the sediment boundary layer tends to be regarded laminar in the $k$-$\omega$ turbulence model because the influence of positive cross-diffusion is larger than that of negative cross-diffusion. This results in a smaller model that can forecast a deeper depth of sediment scour.

**Artificial Neural Network (ANN) Model**

An artificial neural network (ANN) is a programming technique inspired by the organization of the human nervous system. Samadi et al., 2020 claim that complicated nonlinear interactions concealed in data can be understood using ANNs. ANNs can analyze simulation errors from input and output data processed in machine learning to increase the accuracy of the data you wish to forecast. A network design, the number of layers, the kind of activation function, and the type of learning method are just a few of the ANN factors that can be used to determine the accuracy level of an ANN.
an input layer, process them in the hidden layer in this manner, and then process them again in the output layer to create the output.

Hu et al. (2020b) claim that the decision regarding the number of ANN inputs will have a substantial effect on the precision of the prediction outcomes. According to (Sumer & Fredsøe, 1999), dimensionless parameters that have been simplified from dimensional parameters are the input parameters that determine sediment scour in subsea pipes. Azamathulla & Zakaria (2011) varied the number of inputs to the ANN 1 model by changing the flow velocity ($\bar{q}$), sea depth ($Y$), particle diameter ($d_{50}$), and pipe diameter using these 4 parameters ($D$). 5 shield parameters ($\tau$), depth to pipe diameter ratio ($Y/D$), pipe diameter to particle diameter ratio ($D/d_{50}$) Reynolds number ($Re$), and Froude number are all included in the ANN 2 model ($F$).

Table 2. The comparison of the input variation results (Azamathulla & Zakaria, 2011)

<table>
<thead>
<tr>
<th>Number</th>
<th>Model</th>
<th>Number of Input</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>ANN 1 model</td>
<td>4</td>
<td>1.94</td>
</tr>
<tr>
<td>2</td>
<td>ANN 2 model</td>
<td>5</td>
<td>1.28</td>
</tr>
</tbody>
</table>

Table 2 shows that the error value decreases as the number of parameter inputs increases. This demonstrates that the predictions made using the ANN will be more accurate if the number of input parameters is correct. The comparison of changes in input quantity and its outcome has an impact on the error value.

Hu et al. (2020b) assert that only one hidden layer is required to forecast continuous functions like the scour phenomenon. The flexibility and fault tolerance of the ANN are simultaneously impacted by the quantity of nodes/neurons in the hidden layer. The number of neurons can be determined by $m = \sqrt{n + l + a}$, where $m$ is the number of nodes in the hidden layer, $n$ is the number of nodes in the input layer, $l$ is the number of nodes in the outer layer, and $a$ is between 1-10 the integer.

ANN models are also influenced by activation functions to determine the output of neurons. The relationship between input and output in space and time is mathematically represented by an activation function (Yitian & Gu, 2003). Table 3 compares a variety of activation function types used in artificial neural networks (ANNs), including Tanh-Sig, Log-Sig, and linear activation functions.

Table 3 The comparison of using different activation function ANN (Dorofki et al., 2012)

<table>
<thead>
<tr>
<th>Number</th>
<th>Activation function</th>
<th>Formula</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Teluk Pengeli</td>
<td></td>
<td>Teluk Sayong</td>
</tr>
<tr>
<td>1</td>
<td>Purelin (linier)</td>
<td>$a = n$</td>
<td>0.058</td>
</tr>
<tr>
<td>2</td>
<td>Log-Sigmoid</td>
<td>$a = \frac{1}{1 + e^{-n}}$</td>
<td>0.038</td>
</tr>
<tr>
<td>3</td>
<td>Tan-Sigmoid</td>
<td>$a = \frac{2}{1 + e^{-2n}} - 1$</td>
<td>0.042</td>
</tr>
</tbody>
</table>

According to Table 3, the Tan-Sigmoid and Purelin transfer functions have higher RMSE values than the Log-Sigmoid transfer function. Additionally, because of its differentiable qualities, the Log-Sigmoid transfer function is frequently utilized in ANNs that employ the backpropagation algorithm. This is the rationale for the Log-Sigmoid transfer function’s suitability for forecasting scour depth in CFD procedures.

The ANN learning process involves weight updates, backward updates, and forward updates. Bidirectional associative memory, Hopfield networks, and backpropagation (BP) are a few examples of artificial neural network learning techniques. In their study, Hu et al. (2020b), they created a BP model for genetic algorithm (GA)-based scour depth prediction optimization. The weights and constraints of each neuron can be seen worldwide using GA’s global search feature. Consequently, it is possible to enhance the BP ANN model's network convergence speed, accuracy, and stability.
formulations of Moncada-M and Aguirre-Pe (1999) and the conventional BP ANN are then contrasted with the GA-BP ANN model, with the comparison findings displayed in Table 4.

Table 4. Performance evaluation by using GA-BP model (Hu et al., 2020b)

<table>
<thead>
<tr>
<th>Number</th>
<th>Method</th>
<th>R</th>
<th>RMSE</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>GA-BP</td>
<td>0.9437</td>
<td>0.1072</td>
<td>0.0788</td>
</tr>
<tr>
<td>2</td>
<td>BP</td>
<td>0.8281</td>
<td>0.2323</td>
<td>0.1736</td>
</tr>
<tr>
<td>3</td>
<td>Empiric's 1 Formula</td>
<td>0.7605</td>
<td>0.2662</td>
<td>0.1730</td>
</tr>
<tr>
<td>4</td>
<td>Empiric's 2 Formula</td>
<td>0.7416</td>
<td>0.2790</td>
<td>0.2015</td>
</tr>
</tbody>
</table>

Table 4 shows that the GA-BP ANN model performs better than other models. Hu et al., (2020b)'s correlation and error study further demonstrated the GA-BP ANN model's high prediction accuracy and suitability for modeling.

**CFD-ANN Model to Predict Sediment Grading Accurately**

The CFD-ANN approach has been applied in a variety of disciplines, but Pandya et al. (2017)'s investigation of solid particle erosion prediction shares the same fundamental scour mechanism, which is the movement of sediment as a result of flow. The study created a CFD simulation with a geometric model based on the Baker Hughes ERC-2008 experimental model, the Lagrangian technique of sediments as the flow model, and a k-ε turbulence model as the flow model. In order to forecast erosion rates, an ANN model was fed the output of the CFD simulations. The ANN model employed is a multilayer feedforward BP with a Tan-Sigmoid activation function and the Lavenberg-Marquardt learning algorithm. The average error was lowered from 27% to just 7% using CFD-ANN.

![CFD-ANN Model Diagram](image)

Figure 4. The CFD-ANN model

The CFD-ANN combined model thus has an undeniable great potential to increase the subsea pipeline scour forecast accuracy. Considering that the CFD model is similar to estimating silt scour in underwater pipes and that there are numerous parameters. As seen in Figure 4, the layer model of sediment grinding in a subsea pipeline serves as the basis for the CFD-ANN working application model. To achieve CFD simulation results, CFD simulations can be carried out using the k-ε turbulence model method as the flow model and the Lagrangian method as the flow model for the sediment model. As was already indicated, good. In order to analyze the simulation data, the CFD simulation results are input into the ANN. The GA-BP learning technique created by Hu et al. (2020b) and the Log-Sigmoid activation function (Dorofki et al., 2012) are both employed in the multi-layer feed-forward ANN model that was used to predict sediment scour of undersea pipes.
4. Conclusion
The definition of the flow model has a significant impact on the prediction outcomes of the CFD approach, according to the results of the acquired analysis. The complexity of the turbulent flow that takes place during sediment washout is not adequately reflected by the flow model equations currently in use. As a result, it is less reliable at estimating the scour depth of subsea pipes. ANN and CFD approaches can be combined to increase accuracy, lowering the error value of CFD prediction findings by 20%. Prediction accuracy is best achieved using an ANN model with five inputs, Log-Sigmoid activation function, and GA-BP learning algorithm. The use of predictive calculations with a combined CFD-ANN approach demonstrates that engineers in the oil and gas sector have a high chance of reducing the risk of failure due to sediment washout.

References


